Crop Classification with Satellite Imagery

Channel Islands
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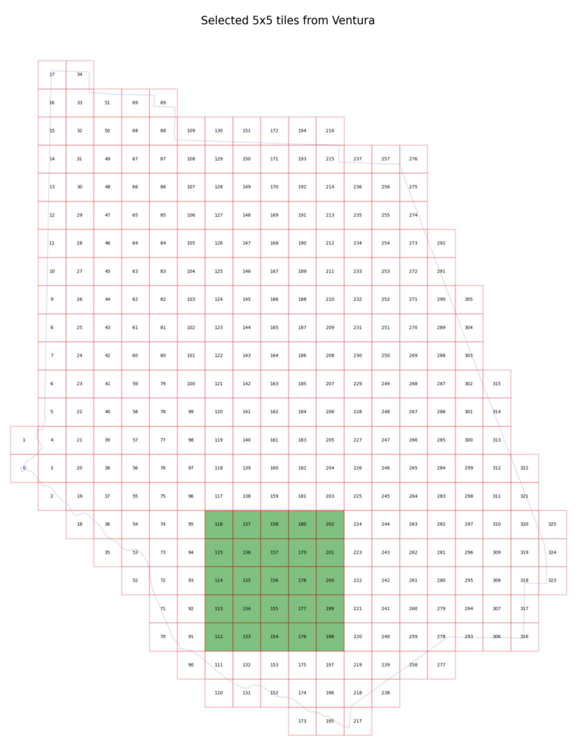

Figure 1. Ventura County Bounding Box

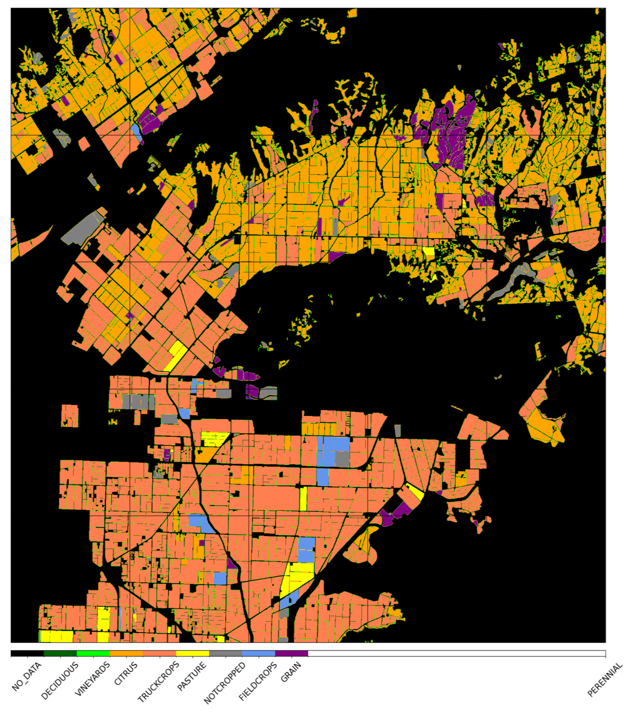

Figure 2. Green section from Figure 1 with crop data overlayed.

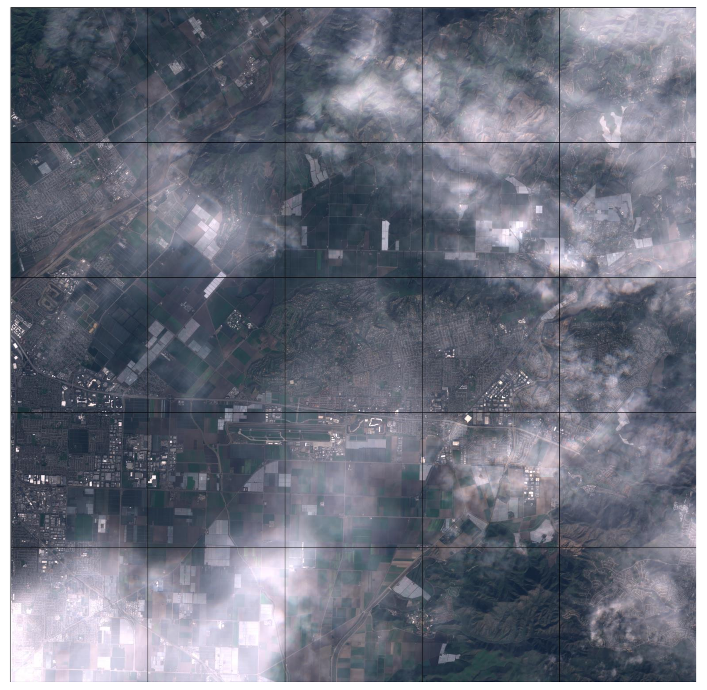

Figure 3. Ventura Satellite Imagery before filtering

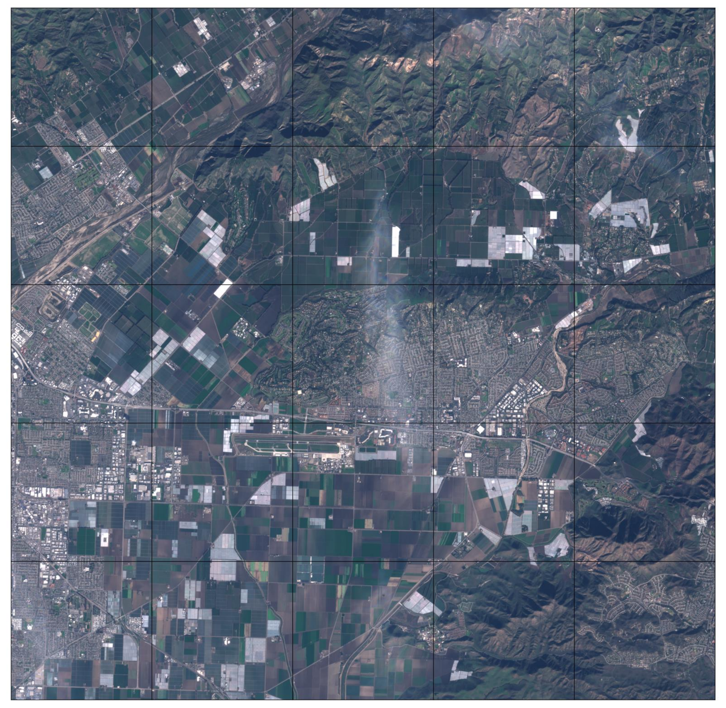

Figure 4. Satellite Imagery after filtering clouds

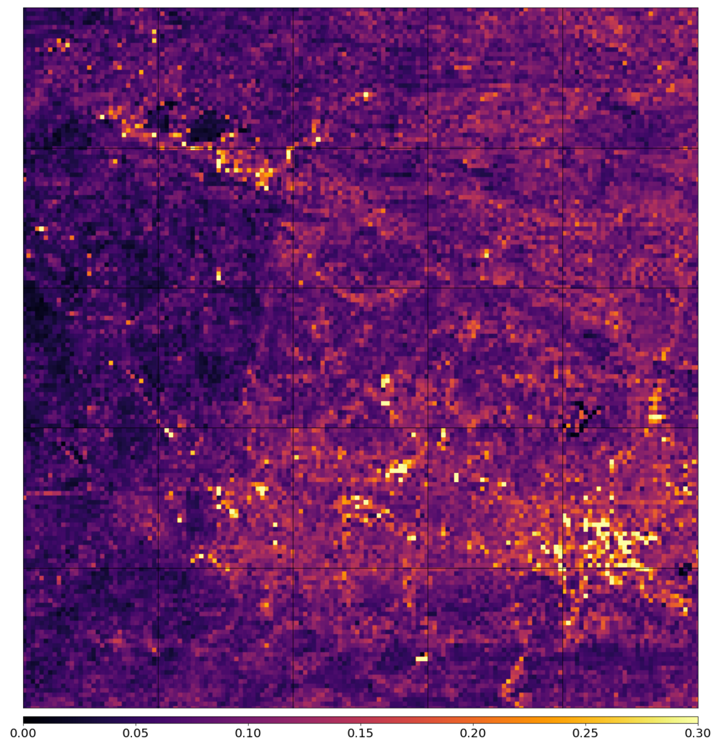

Figure 5. Calculating cloud probability.

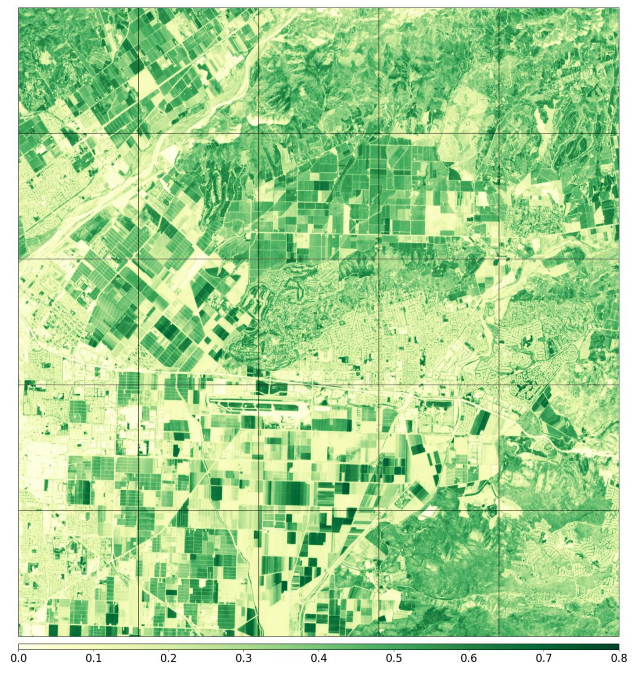

Figure 6. NVDI showing vegetation health.

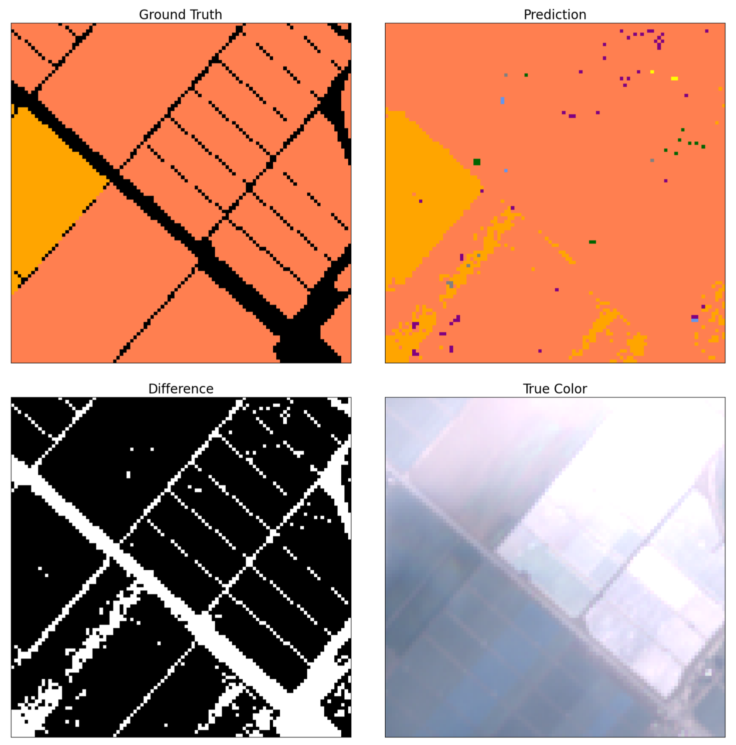

Figure 7. Model prediction results zoomed from a single test box.

Introduction

This project explores the potential of machine learning and geospatial data in environmental monitoring for sustainable agriculture and ecological conservation. It focuses on the development of a system for crop detection and classification, providing insights for optimizing agricultural practices. Beyond its applications in agriculture, this technology holds significant potential for broader environmental monitoring initiatives. By correlating extracted features from satellite imagery with environmental parameters such as land cover, vegetation indices, and water quality, it can support habitat loss prevention, assess ecological changes, and contribute to overall ecological conservation efforts.

Methodology

A systematic approach was employed to collect and analyze data, specifically focusing on utilizing satellite data and known crop information to train a model for crop detection based on extracted features. The initial steps involved gathering relevant information about Ventura County, such as a county outline and crop data in GeoJSON format. This data was then formatted and processed using Jupyter Notebooks and the Python package Eo-Learn.
With the help of Eo-Learn, the county was divided into smaller regions, see Figure 1, to facilitate more localized analysis. First crop data was laid over the divided section, see Figure 2. Then, satellite data from the Sentinel-Hub was downloaded and overlaid on top of the specified region, shown in Figure 3. After downloading the data, it needed to be cleaned up. This included removing any cloud cover as seen in Figure 3 and 4. Cloud masks and cloud probabilities were then generated using the s2cloudless package (includedf in Eo Learn) to identify and filter out cloudy pixels, see Figure 5. By combining the satellite data with the known crop data, a model was trained to detect crops based on the extracted features. One of the features used to classify crops is the NVDI which can also be used to show vegetation density and health, see Figure 6. The model utilized machine learning techniques to learn patterns and relationships between the satellite data and the crop types. The use of satellite data and the integration of known crop information in this approach allowed for data-driven analysis of crop distribution. This approach showcases the potential of combining remote sensing data with existing crop information to enhance crop monitoring and management practices.

Results

The results of the crop detection model were generally positive, accurately identifying and labeling most crop sections, see Figure 7. The model demonstrated a strong capability to analyze visual patterns and features associated with various crops, leading to a successful recognition and classification of the majority of crops. However, there were instances where misclassifications occurred. The limited availability of specific crop data, despite using data from the state of California, contributed to these inaccuracies. More detailed and comprehensive crop data would have improved the model's ability to distinguish between visually similar crops. Incorporating detailed data would enhance the model's precision by capturing crop-specific characteristics.

Conclusions

The results obtained highlight the effectiveness of remote sensing in detecting and labeling crops. The successful identification and classification of crop sections demonstrate the potential of remote sensing as a valuable tool in agricultural monitoring. I plan to continue pursuing this project and expand it to encompass environmental monitoring objectives. By using data such as, Normalized Difference Vegetation Index, Figure 6, remote sensing can assess vegetation health, detect stress conditions, and monitor overall environmental well-being. I also plan to add on the ground sensors using Arduino boards to gather additional data. Integrating these tools enables the tracking of environmental changes, evaluation of land use practices, and support for sustainable management strategies. Expanding the project to environmental monitoring provides insights for risk assessment, land-use planning, and conservation efforts. In conclusion, remote sensing offers tremendous potential in agriculture and environmental monitoring, allowing for effective management and conservation of natural resources.

Literature Cited

Eo-Learn Land Cover Classification:
https://medium.com/sentinel-hub/land-cover-classification-with-eo-learn-part-1-2471e8098195
An amazing guide going over Eo-Learn and how to use it to classify Land Cover.

Eo-Learn: https://github.com/sentinel-hub/eo-learn
A collection of tools in python used for spatial data analysis. This package includes tools for every part of the workflow from downloading data, and extracting features, to training the model. They have amazing guides and resources that explain how to use the tools.

Sentinel Hub: https://www.sentinel-hub.com/
Tool for downloading Satellite data from Sentinel-2. They offer an API the allows users to download current or past satellite data and easily integrates with Eo-Learn.

Acknowledgements

The availability of high-quality satellite data provided by Sentinel Hub has allowed us to gain valuable insights and conduct in-depth analysis. Thank you for your generous sponsorship of a year's worth of satellite data for my project.